

An R Package to Visualize and Communicate Uncertainty in Seasonal Climate Prediction

M.D. Frías^{a,*}, M. Iturbide^b, R. Manzananas^b, J. Bedia^a, J. Fernández^a, S.
Herrera^a, A.S. Cofiño^a, J.M. Gutiérrez^b

^a*Grupo de Meteorología. Dpto. de Matemática Aplicada y Ciencias de la Computación.
Universidad de Cantabria. Avda. de los Castros, s/n. 39005. Santander. Spain*

^b*Grupo de Meteorología. Instituto de Física de Cantabria (IFCA). CSIC - Universidad de
Cantabria. Avda. de los Castros, s/n. 39005. Santander. Spain*

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Abstract

Interest in seasonal forecasting is growing fast in many environmental and socio-economic sectors due to the huge potential of these predictions to assist in decision making processes. The practical application of seasonal forecasts, however, is still hampered to some extent by the lack of tools for an effective communication of uncertainty to non-expert end users. `visualizeR` is aimed to fill this gap, implementing a set of advanced visualization tools for the communication of probabilistic forecasts together with different aspects of forecast quality, by means of perceptual multivariate graphical displays (geographical maps, time series and other graphs). These are illustrated in this work using the example of the strong El Niño 2015/16 event forecast. The package is part of the *climate4R* bundle providing transparent access to the ECOMS-UDG climate data service. This allows a flexible application of `visualizeR` to a wide variety of specific seasonal forecasting problems and datasets.

Keywords: `visualizeR`, Probabilistic visualization, Seasonal forecast, R

*Corresponding author: Grupo de Meteorología. Dpto. de Matemática Aplicada y Ciencias de la Computación. Universidad de Cantabria. Avda. de los Castros, s/n. 39005. Santander. Spain

Email address: mariadolores.frias@unican.es (M.D. Frías)

1. Introduction

Seasonal forecasts (see e.g. Doblas-Reyes et al., 2013) provide, a few months in advance, information on how weather is likely to evolve. Seasonal forecasting is a problem of probabilistic nature, due to the non-linear and chaotic character of the climate system, which renders the state of the atmosphere at this time scale very uncertain, and only predictable statistically and conditioned to the state of slower-response components such as the ocean. *Ensemble* forecasting (Leutbecher and Palmer, 2008) is used to sample this inherent uncertainty by slightly perturbing the initial conditions, as given by the available observations. These forecasts are operationally produced using global climate models, which simulate the state of the ocean and atmosphere (at a coarse resolution of 50-100km) for the coming months (e.g. next season), starting from this ensemble of initial conditions. The resulting ensemble of simulated weather realizations (ensemble members) allows estimating the likelihood of different events/indices related to the seasonal average weather (e.g. being wetter than usual). Therefore, seasonal predictions are intrinsically probabilistic (e.g. “there is an 80% chance that the next season will be wetter than usual in central Spain”), in contrast with deterministic weather forecasts (e.g. “tomorrow it will rain 15 mm in Madrid”).

Despite the growing interest of climate services in seasonal forecasts and the potential value of these predictions for many sectors (hydrology, agriculture, health, etc.), there are still a number of problems which limit the practical application of this type of predictions. Obviously, a seasonal forecast in itself has no value without an indication about how much the predictions can be trusted, being thus essential to provide measures of the *quality* of the seasonal products. Forecast quality is multi-faceted with performance measures providing complementary information on different aspects of forecast quality (association, accuracy, reliability, etc.). It should be noted that the concept of “best” or “good” forecast is subjective and can vary between users with different requirements from the predictions (Murphy, 1993). An evidence-based approach for assessing

forecast quality is to evaluate the performance using a paired data sample of past forecasts and observations, a process known as *forecast verification* (Jolliffe and Stephenson, 2003). Forecast verification provides users with information about possible skill (quality) in future forecasts. Forecasters can also provide users
35 with probabilistic forecasts to help explicitly quantify uncertainties more dynamically. However, such probabilities are non-trivial to define from numerical model outputs (see e.g. Siegert et al., 2016; Primo et al., 2009), and can easily be misunderstood by decision-makers (Lorenz et al., 2015). For these reasons, the probabilistic communication of uncertainty in seasonal forecast products has
40 been highlighted as a major challenge in the practical application of seasonal predictions in different economic sectors (see e.g. Mason, 2008; Lemos et al., 2012; Raftery, 2016).

A proper validation of these probabilistic forecasts requires the use of a set of complementary verification measures (Murphy, 1993) and the availability of retrospective seasonal forecasts, known as *hindcast*, covering a long period (ideally,
45 over 30 years). The hindcast is used to build trust (or not) in the probabilistic forecast system issuing an actionable future forecast. A strong *signal* in a future forecast (i.e. very high or low probability of occurrence for an event) is useless or even dangerously misleading, if the forecast system has no *skill* in
50 predicting such events, something revealed by analysing the historical hindcast performance. For this reason it is recommended to blend forecast information with the verification results of the forecast system, as an indication of its past performance. Due to the different alternative forecast systems and skill scores, and the various intermediate data processing steps involved (spatio-temporal
55 aggregations, regridding/interpolation, bias correction ...) the validation process is application-dependent and prone to error, so tailored solutions rooted on the latest research are required in order to obtain comprehensive and actionable information of model performance for particular end user applications.

Users have to deal with different types of uncertainty in seasonal forecasts.
60 On the one hand the intrinsic uncertainty given by the probabilistic character of the forecast (which may render it non informative in some cases). On the

other hand, the credibility of the forecast system, which can be estimated using forecast verification. This article introduces the R package **visualizeR**, which aims at the visual communication of probabilistic forecasts together with different aspects of forecast quality (in particular accuracy and reliability) with different levels of complexity, thus targeting a wide range of users with varying expertises. A number of existing R packages provide different verification measures for probabilistic forecasts, some of them also implementing standard graphical verification tools, such as reliability plots, ROC curves or rank histograms. Among them, it is worth mentioning **verification** (NCAR - Research Applications Laboratory, 2015), **SpecsVerification** (Siegert et al., 2017) or **easyVerification** (MeteoSwiss, 2017), which implement several state-of-the-art methods. In addition, **ternvis** (Jupp et al., 2012) is an R package that includes a function for visualising ternary probabilistic forecasts in a map. This package defines a continuous colour palette in barycentric coordinates for the map. Even though this idea has a very clear scientific purpose, it may complicate the understanding of the verification to non-expert users. Furthermore, most of these packages mainly include verification or calibration functions mostly focused on users with expert knowledge. However, there is a lack of applications focused on the visual communication of probabilistic verification that can be easily interpreted by users and decision-makers from different sectors that are not necessarily experts on forecast verification.

In order to fill this gap, the **visualizeR** package builds on the user feedback from different environmental sectors and the experience gained during the EU FP7 project EUPORIAS (Buontempo and Hewitt, 2017, <http://euporias.eu>), aimed at the provision of actionable climate information, and maximise the usefulness of seasonal-to-decadal climate information through close collaboration with end users. **visualizeR** goes beyond the currently existing verification tools, combining multiple verification measures in multivariate graphical displays achieving flexible verification diagrams able to effectively communicate the skill of probabilistic forecast predictions. It includes spatial maps, time series representations and single-site displays, addressing different aspects of the

forecast quality. Most of the visualizations available in the package conveniently blend the forecast quality based on the past performance of the forecasting system with the current operational forecast. These characteristics make a difference with respect to other existing probabilistic verification software packages.

`visualizeR` has been developed in R (R Core Team, 2017), a popular computing environment and language among users of climate information. Furthermore, R is Open Source, and benefits from the excellent capabilities of other popular packages for data visualization and geospatial analysis, such as `lattice` (Sarkar, 2008), `fields` (Nychka et al., 2015), `vioplot` (Adler, 2005) and `sp` (Pebesma and Bivand, 2005; Bivand et al., 2013), from which it imports functionalities. The code is distributed to the community through a public GitHub Repository (see Supplementary Material for installation details), thus facilitating code sharing and collaborative development in order to optimally adapt the package to the user’s needs.

In the following sections, we describe the use and functionalities of the package using as illustrative example the NCEP Climate Forecast System version 2 (CFSv2; Saha et al., 2014), and its prediction for the recent *El Niño* 2016 event (Trenberth, 1997). All data required for this example are available from the package, but they can also be independently retrieved from the ECOMS-User Data Gateway (Cofiño et al., 2017), a climate service with an R interface –the **climate4R** bundle– within which `visualizeR` is seamlessly integrated (see Sec. 2). Several examples to access different climate datasets using R are further illustrated, enabling a flexible application of `visualizeR` to a wide variety of specific seasonal forecasting problems.

2. visualizeR as part of the climate4R bundle

The integration of seasonal predictions in different impact sectors (agriculture, energy, hydrology, health . . .) requires data from different sources, including observations, reanalysis and seasonal predictions/hindcasts from state-of-the-art forecasting systems. The ECOMS User Data Gateway (ECOMS-UDG,

<http://www.meteo.unican.es/eoms-udg>; Cofiño et al., 2017) was developed in the frame of the ECOMS (European Climate Observations, Modelling and Services) initiative (the EUPORIAS Project is part of it, see Buontempo and Hewitt, 2017) in order to circumvent all the problems associated with data harmonization, data access policies and complex file/data structures inherent to seasonal forecast data products. The climate4R bundle is an open source, R-based interface for data access and transformation composed by a number of R packages implementing harmonized (one single vocabulary) data access to the ECOMS-UDG (`loader` and `loader.ECOMS` packages, Cofiño et al., 2017)), data collocation including regridding, temporal aggregation, subsetting, etc. (`transformer` package, Bedia and Iturbide, 2016), bias adjustment and downscaling (`downscaleR` package, Bedia et al., 2017b), as well as blended visualization of probabilistic forecasts and quality measures, the latter implemented in `visualizer`. There is full interoperability between the different packages of the climate4R bundle, allowing any user to apply the `visualizer` capabilities to any particular problem considering different variables, geographical regions, lead time predictions, seasons, time periods, reference observations, forecast systems, reference grids, etc., with flexibility and ease of use. This provides a unique comprehensive framework for end-to-end applications of seasonal predictions, hence favouring the reproducibility of the ECOMS scientific outcomes, extensible to the whole scientific community.

A brief example on how to load the data from the ECOMS-UDG using the package `loader.ECOMS` from the climate4R bundle is provided in Section 5. Its usage and features are further described by Cofiño et al. (2017) and Bedia et al. (2017a), and their respective companion documents with worked examples. All the climate4R packages are available through the SantanderMetGroup public GitHub Repository. In particular, the package `transformer` is required to reproduce the examples shown next. Version 1.0.1 of this package is considered here.

3. An application example: El Niño 2015-16

We consider the global seasonal forecast of surface air temperature issued by CFSv2 for the boreal winter 2015/16. This is a case of strong El Niño conditions (Ramsayer, 2016), which lead to increased predictability, as we shall see in the following visualizations of forecast skill. It is worth noticing the practical interest of the selected case study, since a wide range of natural hazards such as typhoons, floods, landslides or droughts, are directly related to El Niño. Therefore, in the light of El Niño predictability documented in previous studies (see, e.g., Manzananas et al., 2014), some of these adverse impacts could be partially mitigated by taking advantage of suitable (i.e. skilful) seasonal forecasts. However, the validation of this type of forecasts is a multi-faceted task which requires the use of various scores accounting for the different aspects of forecast quality: accuracy, reliability, etc.

In order to assess the seasonal forecast quality, a hindcast of past forecasts issued by the same system is required. This covers the period 1983-2010. Both in the hindcast and forecast, we consider an ensemble of 24 members (forecast realizations) and focus on the boreal winter season (December through January) with one month lead time (i.e. forecasts are initialized in November).

Finally, past observations covering the same period as the hindcast are also required as reference to assess the forecast quality. That is, to know whether the event forecast occurred or not. For this purpose, we use the NCEP/NCAR Reanalysis (Kalnay et al., 1996).

These three global data sets (forecast, hindcast and observations) are included in `visualizeR` as built-in example data sets, although these and other data sets can be loaded from the ECOMS-UDG (see Section 5 and Supplementary Material). These data are formatted as a list including all metadata required by the plots (time, location information, meteorological variable, units, etc.). This metadata format is compliant with the `climate4R` bundle.

4. Available visualizations in VisualizeR

`visualizeR` implements different visualizations to address different aspects of the forecast system quality. Most of them show a particular seasonal forecast along with the past forecast system quality for such events. The package includes spatial maps (bubble plot and reliability map) or single-site displays that represent a single point or the spatial average over a homogeneous region (tercile plot, tercile bar plot, spread plot and reliability diagram). Historical forecast probabilities are only shown in the tercile plot where individual historical hits and misses can be directly assessed, other plots (except reliability diagram/map) just present probabilities for the predicted season. The reliability diagram/map shows probabilities conditioned on the forecasts while in the others they are conditioned on the observation of the event.

The choice of these plots and the incremental visualization options are the result of an initial set of plots selected by seasonal forecasting and visualization experts within FP7 EUPORIAS and additional dialogue with users of different climate impacts communities.

The El Niño 2015/16 event forecast is used in the next sections to present the different visualizations implemented in `visualizeR` through the functions: `bubblePlot()`, `tercilePlot()`, `tercileBarplot()`, `reliabilityCategories()` and `spreadPlot()`. We consider the forecast, hind-cast and observations described in the previous section along with the above functions to blend visualization of probabilistic forecasts and quality measures. The different visualizations performed in this study are based on the data sets included in the `visualizeR` package and are completely reproducible executing the code included as Supplementary Material.

Some functions in `visualizeR` (for instance `bubblePlot()` and `reliabilityCategories()`) require all data on the same grid; therefore, they were first brought to a common grid. Then the spatial resolution was lowered to declutter some of the following global plots (e.g. the bubble plots in Figure 1). Both transformations can be performed by using the `transformer`

package.

210 4.1. Bubble plot

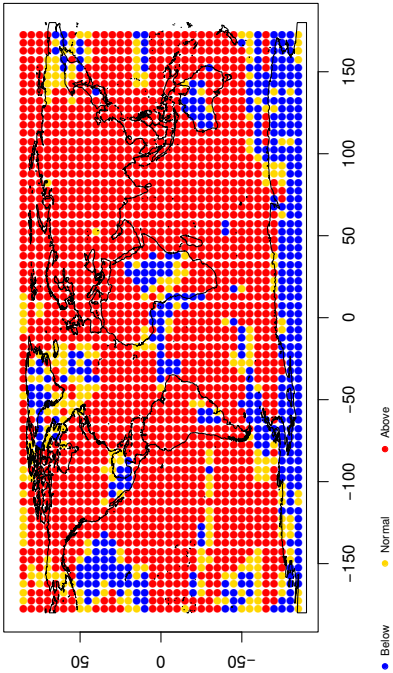
Bubble plots are based on visualisations developed by Slingsby et al. (2009). The `bubblePlot()` function combines in a geographic map several aspects of the seasonal forecast system with different levels of complexity using three properties of the bubbles: colour, size and transparency (Figure 1). This function
215 has two mandatory arguments: the hindcast and the observational data sets. Forecast data set is defined as optional argument. In case the forecast data set is not provided, the last season of the hindcast is displayed as forecast by default, unless a particular year of the historical period is indicated in the optional argument `year.target`. This applies also to other functions, such as
220 `tercilePlot()` and `tercileBarplot()`. Several optional arguments are also available for the `bubblePlot()` function as explained below.

The information most commonly provided at seasonal time scales is the probability of the next season being above, within and below normal conditions. Terciles computed from a long hindcast are used as thresholds to identify these
225 conditions. The simplest display from the `bubblePlot()` function (Figure 1a) just identifies the most likely tercile of the forecast at each grid point using the colour of the bubbles.

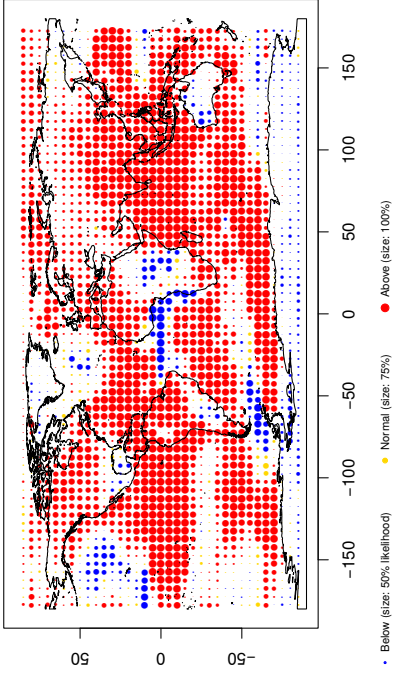
In this example, we analyse temperature, so we use the default colour scale defined as blue for conditions below the lower tercile (colder than normal),
230 yellow for normal conditions and red where above the upper tercile (warmer than normal). However, the colour scale can be chosen by the user with the option `t.colors`. Figure 1a presents the global temperature forecast issued in November 2015 showing a warmer than usual winter in 2016 in most places of the world.

235 We can add information to this plot by adding the probability of the most likely tercile using the size of the bubble (Figure 1b). This is achieved with the optional argument `size.as.probability=TRUE`, which is the default and could be omitted. As reference for the bubble sizes (tercile probability), the legend of

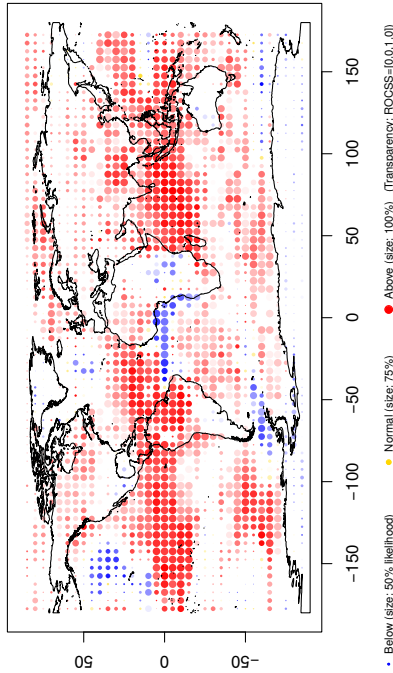
a. 2-meter air temperature, Dec to Feb, 2016
Reference data: NCEP; Hindcast: CFS (24 members); 1983–2010



b. 2-meter air temperature, Dec to Feb, 2016
Reference data: NCEP; Hindcast: CFS (24 members); 1983–2010



c. 2-meter air temperature, Dec to Feb, 2016
Reference data: NCEP; Hindcast: CFS (24 members); 1983–2010



d. 2-meter air temperature, Dec to Feb, 2016
Reference data: NCEP; Hindcast: CFS (24 members); 1983–2010

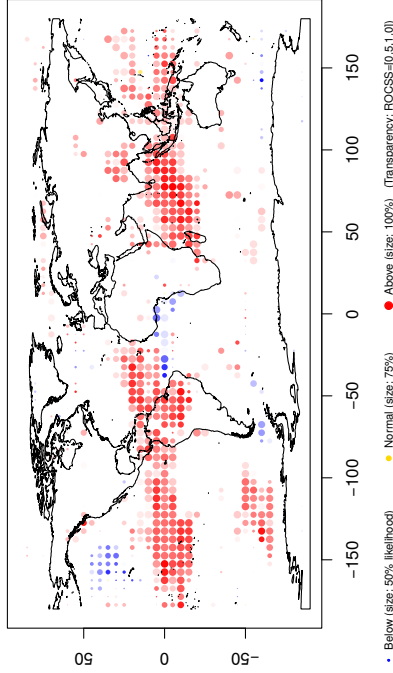


Figure 1: a) Bubble plot for the December, 2015 to February, 2016 2-meter air temperature forecast issued in November, 2015 by the CFSv2 forecast system (24 members). The colour of the bubbles indicates the most likely tercile. b) As a), but representing the probability of the most likely tercile by the size of the bubble. Bubble size for different forecast probabilities are represented in the legend for reference. c) As b), but including ROCSS value as transparency. Forecasts where past skill is worse than the climatology (negative ROCSS) are whitened out. NCEP Reanalysis data is considered as reference to compute the skill score. d) As c), but transparency range only covers ROCSS values from 0.5 to 1 as indicated in the legend.

the figure includes three examples, from 50% to 100% (i.e. all ensemble members
 240 forecast the tercile shown). This option highlights the regions with the highest
 forecast probability (signal) for winter 2016 according to CFSv2; in Figure 1b,
 mainly regions in the tropics directly sensitive to El Niño influence.

The information shown in Figures 1a–b only involves the forecast for a particular
 season (winter 2016); the hindcast has only been used to provide reference
 245 terciles. This signal, however, is not useful unless we have information
 about the skill of the seasonal forecast system, which can be evaluated using
 the whole hindcast period available along with observations. The optional argument
`score=TRUE` (this is the default) allows to evaluate the forecast system by
 computing the Relative Operating Characteristic skill score (ROCSS). ROCSS
 250 measures forecast discrimination for binary events, in this case associated to
 the occurrence of each tercile. This score is commonly used to evaluate the skill
 of probabilistic systems (Jolliffe and Stephenson, 2003). Its value ranges from
 1 (perfect forecast system) to -1 (perfectly bad forecast system). A value zero
 indicates no skill compared to a random prediction. The value of this score
 255 for the most likely tercile is represented by the transparency of the bubbles
 (Figure 1c). By default, only skilful forecasts (positive ROCSS) are shown, as
 indicated in the legend. However, the negative values —the system is worse
 than the climatology— can be highlighted by means of optional arguments.

As expected, the forecast system is more skilful in the tropics (Manzanas
 260 et al., 2017b). Out of the tropics, the skill might appear only conditionally, under
 strong phases of predictability sources such as El Niño (Frías et al., 2010).
 Regions such as North America show high probability for a particular event
 (warmer than normal in winter 2016), but low past skill. The transparency range
 is indicated in the legend and it can be customized using the `score.range` optional
 265 argument. Figure 1d provides an example with `score.range=c(0.5,1)`.
 This option increases contrast on actionable ROCSS values (Rice and Harris,
 2005) and whitens out low skill regions, where the system can show statistically
 significant skill, but cannot be trusted for decision-making. The high skill over
 the tropics is even clearer in this last panel.

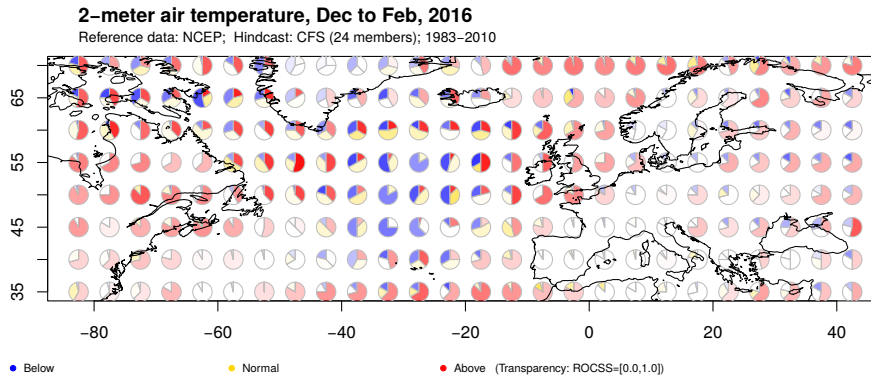


Figure 2: As Figure 1c but including the probability forecast for each tercile as sectors of a 3-piece pie chart in a zoom over the North Atlantic region. Transparency shows the skill score of the probabilistic system for each tercile. Only positive values are plotted

Maps in Figure 1 only present results for the most likely tercile. A pie chart variant (Figure 2) can be plotted showing the probability forecast for each tercile as sectors of a 3-piece pie chart. `bubblePlot()` also includes this possibility by means of the `piechart=TRUE` argument. The skill score as transparency can still be used (`score=TRUE`). In order to discern the pie charts, this variant is more adequate for small regions and/or low resolution gridded data sets. Figure 2 was produced by zooming into the North Atlantic region. To this end, the input gridded data was subset using the `transformR` package (see Supplementary Material).

This zoom over the North Atlantic (Figure 2) shows quite limited skill of the CFSv2 forecast system for surface air temperature over Europe, and some skill over the ocean and the Labrador Peninsula, mainly for the upper and lower tercile. Probabilities for all terciles are shown. With this plot, situations where most ensemble members forecast either warm or cold conditions (with few normal cases) can be identified (e.g. north-east of Canada). Previous plots just show the most likely tercile there (warm), even though the opposite (cold) is also very likely according to the forecast.

4.2. Tercile plot

The tercile plot produced by `tercilePlot()` is based on a plot initially displayed by Díez et al. (2011, their Figure 2). This intuitive plot (Figure 3) presents historical forecast probabilities (as shades) for the three categories (below, normal, above) defined from the historical terciles, along with the category that actually occurred (bullets), according to a reference observational data set. Therefore, individual historical hits and misses can be directly assessed. Forecast sharpness (the degree to which probabilistic forecasts are close to deterministic 0 or 1 forecasts) is also evident in this representation, as a high (sharp) vs. low contrast (no sharpness) shade.

The plot can be constructed for a single location or aggregated (spatial average forecast) over a region. However, it should be used with caution over heterogeneous regions. The spatial average is first computed (with a warning) to obtain a single time series for the whole domain. As an example, the tercile plot over El Niño 3.4 region (5S-5N and 170-120W) is shown in Figure 3.

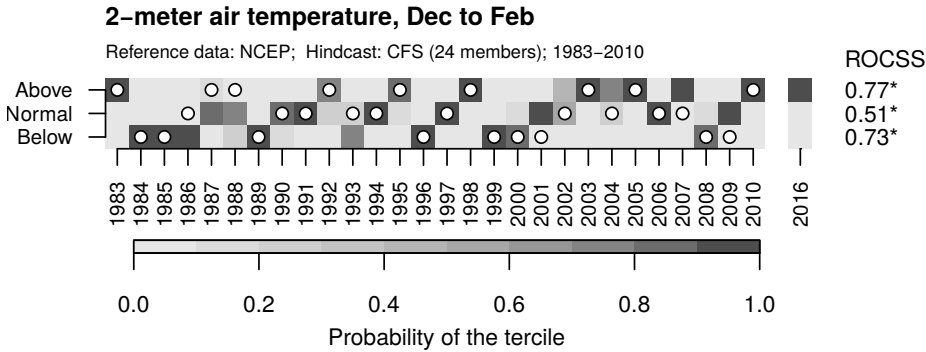


Figure 3: Tercile plot for the same data as in Figure 1 but averaging over El Niño 3.4 region (5S-5N and 170-120W). Shading of each square represents the probability (darker shade=greater probability) for each category (below, normal, above). Dots show the corresponding observed category for each year of the hindcast period. ROCSS values obtained from the hindcast period are indicated on the right side for each category. Significant values with a 95% confidence are marked with an asterisk. Probabilities for the forecast event (winter 2016) are shown slightly separated from the hindcast period.

Only hindcast and observed data sets are mandatory. We can also indicate

the forecast data set as in this example or just select a year within the historical period using the argument `year.target`. In the latter case, the target year will be removed from the hindcast and considered as forecast. Tercile probabilities for the forecast are shown on the right of the tercile plot. The observation is not plotted in this case, given that, in principle, this extra column is intended to communicate a future forecast. Figure 3 shows a winter 2016 forecast with high probability (dark shade) of above normal temperature. This strong signal is useful in combination with the skill of the forecast system that can be evaluated through the historical records for this event also shown in the figure. Here most of the warm (above normal) observed events were predicted by most of the ensemble members.

Tercile plots provide a direct, intuitive assessment of forecast quality, along with the forecast. It also includes a summary score (ROCSS) of forecast quality for each category. Significant values with a 95% confidence are marked with an asterisk. Therefore, tercile plots complement the spatial information represented in the bubble plot by presenting the performance of a seasonal forecast system along a time period. This visualization might help in building the end user understanding of skill scores, given that they are presented along with the actual past forecasts and occurrences of the event. Low ROCSS values, even if statistically significant, could be useless for many applications. However, this representation provides an actual feeling of the accuracy of the forecast system. As a result, tercile plots have been already used in several recent works (Manzanas et al., 2014; Ogutu et al., 2016; Bedia et al., 2017a; Manzanas et al., 2017a).

4.3. Tercile bar plot

Tercile bar plot (Figure 4) is a simple bar plot of the forecast probabilities for each of the three categories defined from the historical terciles. This type of visualization is obtained from the `tercileBarplot()` function. Climatological probability (i.e. $1/3$) is represented by the grey horizontal line as reference. The accuracy of the forecast system for each category is also in-

icated by the ROCSS value. Significant values with a 95% confidence are marked with an asterisk. The score is colour coded to indicate whether there is No Skill (Red), Some Skill (Grey), or Good Skill (Blue); so as provide a salient warning to users where scores are negative. User can choose the threshold to distinguish between the last two categories with the optional argument `score.threshold`. This plot is based on the on-line seasonal temperature and precipitation outlooks issued by MeteoSwiss (<http://www.meteoswiss.admin.ch/home/climate/future/seasonal-outlook.html>).

Figure 4 is an illustrative example representing tercile bar plots for two selected winter events (2016 and 2002) over El Niño 3.4 region. Note that the spatial mean is internally computed by the function and indicated with a warning. However, this plot can also be obtained for a single location. As observed in Figure 3, tercile probabilities for these two events are different: most members of the forecast for 2016 predict a warmer winter than normal, whereas in 2002 probability is almost the same for the above and within normal conditions. These probabilities are shown as bars in Figure 4, along with the ROCSS of the forecast system for each category. ROCSS values are slightly different in the figures since 2002 is excluded of the hindcast period in Figure 4b. In any case, the skill of the forecast system over this region is very high as already shown in previous sections.

4.4. Reliability diagrams and categories

Reliability diagrams plot the observed frequencies of a particular event (e.g. the warm tercile) as a function of its forecast probability, appropriately binned (see Doblas-Reyes et al., 2008, for details). Since they show probabilities conditioned on the forecasts (i.e., given that the event was predicted, what was the observed outcome?), reliability diagrams are a good partner to the ROCSS, which is conditioned on the observations (i.e., given that the event occurred, what was the corresponding forecast?).

In `visualizeR`, the function `reliabilityCategories()` produces this type of plot. In this visualization it is intended to evaluate the skill of the forecast

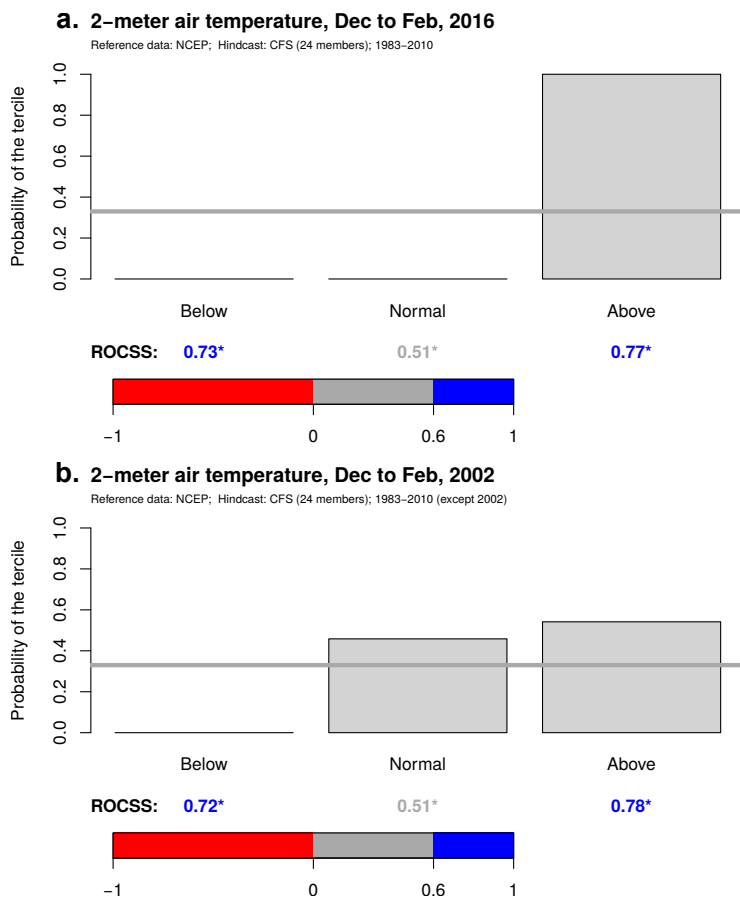


Figure 4: Tercile bar plot over El Niño 3.4 domain. Bars represent the predicted likelihood of each tercile for the forecast event (winter 2016 in a and winter 2002 in b) relative to climatology represented by a grey horizontal line (e.g. 33.3 percent). ROCSS values obtained from the hindcast period are indicated numerically at the bottom of each bar. Significant values with a 95% confidence are marked with an asterisk. This score is colour coded to indicate whether there is No Skill (Red), Some Skill (Grey), or Good Skill (Blue)

system and not that of a particular forecast in contrast to other visualization functions of the package. For instance, Figure 5 shows the reliability diagrams obtained for cold, normal and warm conditions in El Niño 3.4 region using the same hindcast and observations as in previous sections. Note that instead of considering the spatial averages and in order to increase the sample, both observations and predictions for all grid boxes within the region of interest are pooled into a unique time-series from which reliability diagrams are computed. Whereas the diagonal —indicated by a dashed grey line— would mark the perfect reliability, points falling in the so-called skill region (shaded in grey) still contribute positively to the forecast skill. The reliability line (solid black line) that best fits the points in the diagram is obtained by means of least squares, and it is weighted by the number of forecasts in each bin (represented by the size of the points). A confidence interval for the slope of this line (coloured region in each panel) is computed by means of bootstrapping. Many aspects of these diagrams can be customized via optional arguments (see Supplementary Material).

Based on the relative position of the reliability line and the uncertainty range around it, Weisheimer and Palmer (2014) proposed a user-oriented scale with five reliability categories: *perfect* (green), *still very useful* (blue), *marginally useful* (yellow), *not useful* (orange) and *dangerously useless* (red). Moreover, within the *marginally useful* (yellow) category, Manzananas et al. (2017b) differentiated those cases in which the reliability line lies within the skill region, assigning to this new category (*marginally useful +*) the dark yellow colour. Note that the colours corresponding to these six categories are provided in the diagrams produced by `reliabilityCategories()`, along with the label that identifies the reliability category.

Furthermore, `reliabilityCategories()` can be simultaneously applied on more than one region. In this case, the argument `regions` can be used to specify a list of regions of interest, which must be given as a `SpatialPolygons` object from the `sp` R package. Reliability diagrams are in this case omitted and summarized by their corresponding reliability category, identified by its

colour code. Some predefined regions, such as the ones introduced in the IPCC
 5th Assessment Report (see http://www.ipcc-data.org/guidelines/pages/ar5_regions.html), are readily available (`regions = AR5regions`). Figure 6
 shows the reliability categories obtained for the 33 AR5 regions for each of the
 three categories.

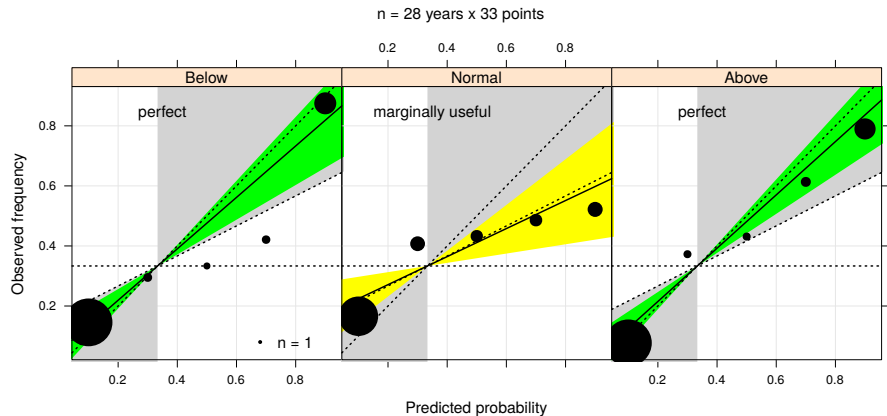


Figure 5: Reliability diagrams obtained for the below, normal and above categories (from left to right) for 2-m air temperature over El Niño 3.4 region. As derived from the size and position (near the diagonal) of the points in the extreme probability bins, the forecast system exhibits a high capacity to discriminate between cold/non-cold events and warm/non-warm ones, leading thus to a *perfect* reliability for the two ‘extreme’ conditions.

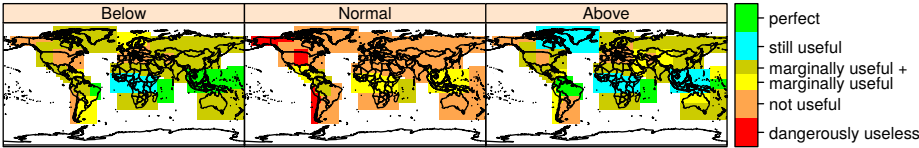


Figure 6: Reliability categories obtained for the below, normal and above categories (from left to right) for the 33 AR5 regions. Note that reliability is in general better in the tropics and for cold and warm events (as compared to normal ones).

5. visualizeR and the ECOMS-User Data Gateway interoperability

The above examples use sample data sets included in `visualizeR`. However, more general data can be retrieved from the ECOMS-UDG climate data service using the `loader.ECOMS` package (Cofiño et al., 2017). For example, we can take advantage of daily data loaded from the ECOMS-UDG to illustrate spread plots, another forecast visualization implemented in `visualizeR` that, unlike the previous ones, requires daily data as input.

Prior to data loading, authentication is required to access the UDG. Note that all data used in this paper are publicly available, and therefore their access is granted after UDG registration. The authentication is performed in one step within R, using the user name and password obtained after registration (see Supplementary Material for details).

Different types of climate data sets can be accessed using the workhorse function `loadECOMS()`, with intuitive arguments required to unequivocally specify the data subset requested. For instance, the argument `dataset` is used to designate the different data sources considered in previous examples: the CFSv2 hindcast data (`dataset="CFSv2_seasonal"`), the operational forecast predictions (`dataset="CFSv2_seasonal_operative"`) and the reference data for verification (`dataset="NCEP_reanalysis1"`). Surface air temperature is indicated with the argument `var` (`var="tas"`) being “tas” the harmonized nomenclature defined by the UDG vocabulary (type the command `loader::UDG.vocabulary()` for an overview of standard variable names and units across all the UDG datasets). The spatial domain to retrieve (e.g. El Niño 3.4 region) is defined with two arguments `lonLim=c(-170,-120)` and `latLim=c(-5,5)`, while the target period of the year (boreal winter) is specified as `season=c(12,1,2)`. The historical hindcast period considered goes from 1983 to 2010 (`years=1983:2010`), and the selected forecast year is 2016 (i.e., the predictions for winter 2016, entailing by convention Dec. 2015 and Jan-Feb. 2016, `year=2016`).

The required hindcast and operational prediction data sets correspond to

the initializations of November (this is, one-month ahead seasonal predictions).

Thus, the argument `leadMonth=1` is also required (this is the default value).

The function `loadECOMS` uses this simple definition of lead time of the prediction, so non-expert users do not need to worry about how the different ensemble members have been generated and their possibly different starting dates. Finally, the number of ensemble members to be loaded can also be defined by the

user. Here, we have considered the first 24 ensemble members.

The advantages of the R interface lie not only in its user-friendly arguments to specify complex data requests, but also in the possibility of performing flexible on-the-fly temporal aggregations (from daily to monthly) best suited to the particular needs of each user. For example, the original CFSv2 model data are archived at 6-hourly time resolution. Through the arguments `time="DD"` (to convert the data from 6-h to daily) and `aggr.d="mean"` (to indicate the aggregation function applied), the user is able to obtain daily mean values directly. This saves the user later work of aggregation, and also prevents potential errors at this stage (temporal aggregations are an error-prone operation due to different calendars, season definitions etc.), and at the same time significantly reduces the memory space occupied by the loaded object if the user is not interested in the highest temporal frequency available, but in time-aggregated data.

Even though a small region has been selected for this example (El Niño 3.4 domain), the complete data loading may take up to a few hours, depending on network traffic, data server load and other factors. In turn, the user benefits from already pre-processed and homogenised data for the target region/season/period of interest, while resorting to the original data source (e.g., the NOAA's NOMADS servers in the case of CFSv2 predictions) is a far more time-consuming task, usually out of the technical capacity for many users of seasonal predictions.

5.1. Spread plots

We consider the daily hindcast and forecast data loaded from the ECOMS-UDG climate data service to introduce spread plots, which require daily data for

their construction. The function `spreadPlot()` produces a plot that represents the spread of monthly mean forecasts (boreal winter 2016 in this case) in box plots (Figure 7a). The background shading represents the climatology for the hindcast period. The shaded areas show the central tercile (dark shade) and the maximum and minimum (light shade). To avoid an excessive visual influence of daily peaks on its interpretation, the daily data is internally smoothed by means of a (centred) moving average of 31 days. Therefore, at the location of the box plots, the background shows the monthly mean forecast (the terciles and extremes being computed over members and years). The box plots can be replaced by violin plots (`violin=TRUE`), to unveil multi-modalities in the data as in Figure 7b for boreal winter 2002.

This plot shows additional information, as compared to the previous visualizations, since it shows absolute values of the variable for the ensemble members, and not probabilities of the terciles. However, it does not show any information related with the observations. The spread of the forecast ensemble for the winter 2016 forecast is very low (Figure 7a) compared, for instance, to winter 2002 results (Figure 7b) when as mentioned before the probabilities for the upper and normal terciles are similar. The temperature forecast for 2016 was extraordinarily high (all members exceeded all previous historical forecasts) and so it was the El Niño event predicted for that season (Ramsayer, 2016), which in the end was not record-breaking as forecast.

6. Summary and prospect

We presented the recently-developed R package `visualizeR`, aimed at interfacing between state-of-the-art probabilistic seasonal forecast systems and end users of these mid-range climate forecasts. This package provides a powerful tool for end users to explore the forecasts and get a grasp on their uncertainty. By design, the visualizations exhibit different levels of complexity and present the same forecast from different points of view, to reach a wide end user audience. This makes a difference with respect to other existing probabilistic verification

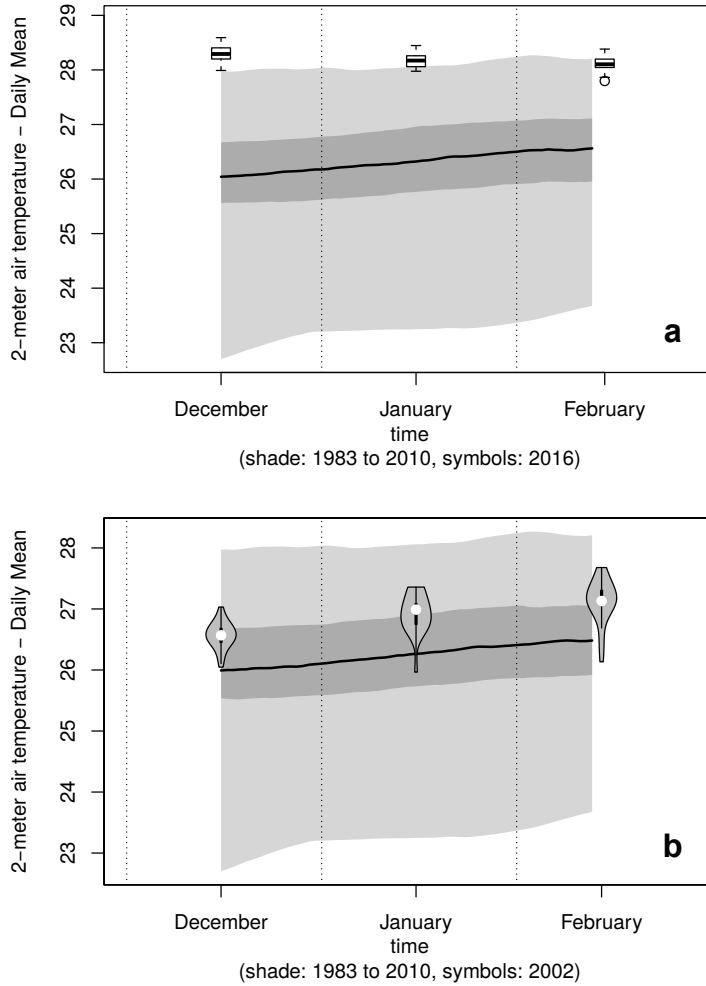


Figure 7: a) Spread plot (see text) for boreal winter 2016 temperature, spatially averaged over El Niño 3.4 domain, according to the CFSv2 forecast system. b) As a), but showing the forecast for boreal winter 2002. Here the spread of the forecast is represented by violin plots.

software, usually aimed for expert climate users.

The visualizations are based on end user feedback from different sectors, gathered during the EU FP7 project EUPORIAS. In the context of this and the companion SPECS project, a full set of climate postprocessing tools have been developed in the R language (climate4R bundle), already well established in the climate science community and increasingly adopted by users of climate information in different sectoral applications. `visualizeR` is fully integrated into climate4R, thus providing full interoperability with seasonal forecast data access and transformation tools. The visual communication of uncertainty to end users is nowadays a cornerstone of climate services, boosted by a number of projects and initiatives which will provide new feedback on end users demands. `visualizeR` is a live and open project aiming to implement new visualizations oriented towards end users understanding and decision-making based on seasonal probabilistic forecasts.

Acknowledgements

This work has been funded by the European Union 7th Framework Program [FP7/20072013] under Grant Agreement 308291 (EUPORIAS Project). We are grateful to the EUPORIAS team on Communicating levels of confidence (Work Package 33) led by Andrea Taylor and Suraje Dessai, who provided feedback from the users to improve the visualizations implemented in this R package. We are also grateful to Aidan Slingsby, who inspired us in new ways of visualizing probabilistic forecast uncertainty. J.M. Gutiérrez thanks Antje Weisheimer and Tim Palmer for the enjoyable stay at the University of Oxford, getting in touch with reliability categories.

Software availability

Name of the software: `visualizeR` (version 1.0.0).

Year First Available: 2016.

Developers: M.D. Frías, M. Iturbide, R. Manzananas, J. Bedia, J. Fernández, S.

Herrera, A.S. Cofiño, J.M. Gutiérrez.

E-mail: mariadolores.frias@unican.es

Website: <https://github.com/SantanderMetGroup/visualizeR>

Hardware Requirement: General-purpose computer.

520 Programming Language: R.

Software Requirement: R version 3.1.0 or later.

Licensing

This software is made freely available under the terms and conditions of the GNU General Public License Version 3.

525 Data availability

Daily data considered in Section 5.1 can be retrieved from the ECOMS-UDG (see Section 5). The two specific datasets used can also be directly downloaded from:

<http://meteo.unican.es/work/visualizeR/data/tas.cfs.dly.rda>

530 <http://meteo.unican.es/work/visualizeR/data/tas.cfs.operative.dly.2016.rda>

All other monthly data used are available in the package.

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Appendix A. Supplementary data

```
660 #
    # Supplementary Material
    # R code to reproduce the application example for El Nio 2015-16
    #

665 # Installation

install.packages('devtools')
library(devtools)
devtools::install_github(c("SantanderMetGroup/transformeR@v1.0.1",
                           "SantanderMetGroup/visualizeR"))

670 library(visualizeR)
library(transformeR)

# Data load
data(tas.cfs)
675 data(tas.cfs.operative.2016)
data(tas.ncep)

# Adjusting data spatial resolution to 5 lat-lon resolution
newgrid <- getGrid(tas.cfs)
680 attr(newgrid, "resX") <- 5
attr(newgrid, "resY") <- 5
lower.res <- function(x, newgrid) {
    interpGrid(x, new.coordinates = newgrid, method = "bilinear",
    bilin.method = "fields")
685 }

obs <- lower.res(tas.ncep, newgrid)
hindcast <- lower.res(tas.cfs, newgrid)
forecast <- lower.res(tas.cfs.operative.2016, newgrid)
```

```

690
#
# Bubble plot (Figure 1)
#
subtitle <- sprintf("Reference data: NCEP; Hindcast: CFS (%d members); %d-%d",
695             length(hindcast$Members),
             getYearsAsINDEX(hindcast)[1],
             tail(getYearsAsINDEX(hindcast),1)
)
# Only colour of the bubble is plotted indicating the most likely tercile
700 bubblePlot(hindcast, obs, forecast = forecast,
             bubble.size = 1.5,
             subtitle = subtitle,
             size.as.probability = FALSE, score = FALSE
)
705 # Added size of the bubble indicating the probability of the most
# likely tercile
bubblePlot(hindcast, obs, forecast = forecast,
             bubble.size = 1.5,
             subtitle = subtitle,
710             size.as.probability = TRUE, score = FALSE
)
# Added transparency of the bubble indicating the ROC skill score (ROCSS)
bubblePlot(hindcast, obs, forecast = forecast,
             bubble.size = 1.5,
715             subtitle = subtitle,
             size.as.probability = TRUE, score = TRUE
)
# Rescale transparency
bubblePlot(hindcast, obs, forecast = forecast,

```

```

720         bubble.size = 1.5,
           subtitle = subtitle,
           size.as.probability = TRUE, score = TRUE, score.range=c(0.5,1)
       )

       # Cropping the North Atlantic region
725 crop.natl <- function(x) subsetGrid(x, lonLim = c(-80, 42), latLim = c(35, 72))
       hindcast.natl <- crop.natl(hindcast)
       forecast.natl <- crop.natl(forecast)
       obs.natl <- crop.natl(obs)

       # Replacing bubbles by sectors of a 3-piece pie chart indicating the probability
730 # of each tercile. (Figure 2).
       bubblePlot(hindcast.natl, obs.natl, forecast = forecast.natl,
                  bubble.size = 1.5,
                  subtitle = subtitle,
                  piechart = TRUE, score = TRUE
735 )

       #
       # Tercile plot (Figure 3)
       #
740 # Cropping El Nio 3.4 region
       crop.nino <- function(x) subsetGrid(x, lonLim = c(-170, -120), latLim = c(-5, 5))
       hindcast.nino <- crop.nino(hindcast)
       obs.nino <- crop.nino(obs)
       forecast.nino <- crop.nino(forecast)
745 # Tercile plot
       tercilePlot(hindcast.nino, obs.nino, forecast = forecast.nino, subtitle = subtitle)

       #
       # Tercile bar plot (Figure 4)
750 #

```



```

# Plot for winter 2016 (forecast data)
tercileBarplot(hindcast.nino, obs.nino, forecast = forecast.nino,
               score.threshold = 0.6, subtitle = subtitle)
# Plot for winter 2002 (selected from the hindcast)
755 year.target <- 2002
    subtitle_year.target <- sprintf("Reference data: NCEP; Hindcast: CFS (%d members);
                                   %d-%d (except %d)", length(hindcast$Members),
                                   getYearsAsINDEX(hindcast)[1],
                                   tail(getYearsAsINDEX(hindcast),1), year.target)
760 tercileBarplot(hindcast.nino, obs.nino, year.target = year.target,
                  score.threshold = 0.6, subtitle = subtitle_year.target)

#
# Reliability categories
765 #
# Diagram (Figure 5)
rl.nino <- reliabilityCategories(hindcast.nino, obs.nino,
                                n.events = 3, labels = c("Below", "Normal", "Above"),
                                n.bins = 5, n.boot = 1000, conf.level = 0.9,
770                                cex0 = 0.5, cex.scale = 20
                                )
# Map (Figure 6)
rl.map <- reliabilityCategories(hindcast, obs,
                                n.events = 3, labels = c("Below", "Normal", "Above"),
775                                n.bins = 5, n.boot = 1000, conf.level = 0.9,
                                regions = AR5regions)

#
# UDG data access
780 # NOTE that data loading from the ECOMS-UDG may take up to a few hours depending on
# several factors (network traffic, temporal and spatial resolution, etc). Daily data

```

```

# for this section can be also retrieved from:
# http://meteo.unican.es/work/visualizeR/data/tas.cfs.dly.rda
# http://meteo.unican.es/work/visualizeR/data/tas.cfs.operative.dly.2016.rda
785 #

# The version of the packages used to reproduce the results of this manuscript
# are installed.
# Note that updated versions can be available in github.
790 devtools::install_github(c("SantanderMetGroup/loader.java@v1.1-0",
                             "SantanderMetGroup/loader@v1.1.0",
                             "SantanderMetGroup/loader.ECOMS@v1.3.1"))

library(loader.ECOMS)
# UDG Authentication
795 loginUDG(username = "", password = "") # Note username and password obtained from
                                         # the UDG registration.

# Load reanalysis
tas.ncep.dly <- loadECOMS(dataset = "NCEP_reanalysis1",
                          var = "tas",
800                          years = 1983:2010, season = c(12, 1, 2), time = "DD",
                          aggr.d = "mean", lonLim = c(-170, -120), latLim = c(-5, 5)
)

# Load hindcast
tas.cfs.dly <- loadECOMS(dataset = "CFSv2_seasonal",
805                          var = "tas",
                          years = 1983:2010, season = c(12, 1, 2), time = "DD",
                          aggr.d = "mean", lonLim = c(-170, -120), latLim = c(-5, 5),
                          leadMonth = 1, members = 1:24      # note 'leadMonth'
                                                                # and 'members'
810 )

# Load operational predictions for winter 2016
tas.cfs.operative.dly.2016 <- loadECOMS(dataset = "CFSv2_seasonal_operative",

```

```

var = "tas",
years = 2016, season = c(12, 1, 2),
815 time = "DD", aggr.d = "mean",
lonLim = c(-170, -120), latLim = c(-5, 5),
leadMonth = 1, members = 1:24 # note 'leadMonth'
                                # and 'members'
)
820 #
# Spread plots (Figure 7)
#
# Plot for winter 2016 (forecast data)
spreadPlot(tas.cfs.dly, forecast = tas.cfs.operative.dly.2016, boxplot = TRUE)
825 # Plot for winter 2002 (year selected from the hindcast)
spreadPlot(tas.cfs.dly, year.target = 2002, violin = TRUE)

```